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Identifying design parameters for fuzzy control of staged ventilation control systems

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Abstract

Conventional staged ventilation systems are commonly used in agriculture to maintain interior environments near desired conditions for livestock housing and greenhouses. This paper identifies design parameters for fuzzy-based control of these staged ventilation systems. A simple non-steady state heat balance is used in conjunction with a broiler house simulation model, and coupled with a model for the control system, to simulate control system performance. Difficulties with implementation of conventional staged ventilation control, and the proposed fuzzy inference technique, arise because of the discontinuous nature of these highly non-linear systems. Comparisons between the new fuzzy stage controller and conventional staged control are made. Effects of varying the identified design parameters for the fuzzy stage controller, including different degrees of control precision and energy use, rule base complexity, and the rate of change of house temperature are made. Results indicate that existing staged ventilation control systems which utilize microprocessors could realize significantly enhanced control flexibility by a simple software modification to incorporate the fuzzy staged controller method. © 2001 Elsevier Science B.V. All rights reserved.

Keywords: Agricultural building; Broiler; Simulation model; Fuzzy logic; Fuzzy control; Thermal environment; Heat flow

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1. Introduction

Staged ventilation systems are commonly used for environment control in livestock facilities and greenhouses in the USA. These systems utilizes a series of discrete stages of ventilation and heating to add air conditioning capacity as the current inside air temperature deviates from a set point. Such a staged control system is highly non-linear, not readily analyzed with classical control techniques, and yet works quite well in many cases. For smaller facilities with adequate or excessive capacity for ventilation-based energy transfer, and low internal heat and moisture loads, only a few stages are generally necessary. Ventilation stages in these instances provide a balance between energy exchange capacity and the thermal needs of the space's occupants (Zhang and Barber, 1993; Chao and Gates, 1996). When outside conditions and internal heat loads are such that desired interior conditions cannot be maintained with the equipment at hand, the resultant deviation from set point is considered acceptable in comparison to costs and complexity of a more optimal control technique (Cole, 1980).

As building sizes have increased, however, there has been a tendency toward a greater number of ventilation stages. This increased stage capacity means that either a larger deviation from set point is accepted for significant periods of operation, or temperature differentials between stages must be reduced. In the latter case, there is a limit to how small the differentials can be made without excessive switching of large ventilation loads. Further, by definition of their operation, such systems require a specified difference between set point temperature and building interior temperature for ventilation to occur; in a sense they behave as 'discrete proportional controllers'. Most commercially available systems used in agriculture have no means for an integral control to bring interior conditions to set point values; an exception is for some greenhouse systems which 'drive to set point' by various ad hoc techniques. Significant research to improve building heating and ventilation control systems can be found in the literature (e.g. Berckmans and Goedseels, 1986; Timmons and Gates, 1987; Allison et al., 1991; Zhang et al., 1993a,b; Chao et al., 1995; Timmons et al., 1995; Chao and Gates, 1996).

Fuzzy logic offers an alternative to conventional stage controllers (Gates et al., 1997). By suitable selection of input/output linguistic variables and a rule base, a broad range of desirable control outcomes can be achieved. Possible features might include user-specified overall control 'tightness' analogous to a control range, closer adherence to set point conditions if desired, and the ability to explicitly set the trade-off between energy costs and interior environment.

A fuzzy inference system (FIS) approach for design of a ventilation control system is developed in this paper. Appropriate design parameters are identified for different degrees of sophistication. Representative systems are simulated and comparisons are made to conventional staged control (CSC) of ventilation. A broiler house model was selected as a candidate test model because both internal heat loads and external disturbances can range over broad degrees, and thus severely test the adequacy of any control system to balance control precision, energy use, and control stability.

2. Simulation models

2.1. Building heating-ventilating model

A simple building heating-ventilating model as depicted in Fig. 1 was constructed (Simulink©, Ver 2.0, The Mathworks Inc., Natick MA 01760-1500). The building model was formed as a masked block with adjustable parameters for the differential equation, which describes a sensible heat balance on the interior volume (Chao et al., 1995):

$$\frac{dT}{dt}=\frac{1}{\rho C_p V}[q_{\text{heater}}+q_{\text{internal}}]-\frac{\dot{V}}{C_p V}(T-T_{\text{out}})-\frac{UA}{\rho C_p V}(T-T_{\text{out}}), \tag{1}$$

where: T is interior temperature, °C; T_{out}, Outside temperature, °C; V, building volume, m^3; UA, heat transfer coefficient, W K^{-1}; ρ, air density, 1.2 kg m^{-3}; C_p, specific heat of air, 1006 J kg^{-1} K^{-1}; Q_{heater}, rate of energy input from heaters, W; Q_{internal}, net sensible energy into building, W; $\dot{V}$, ventilation rate, m^3 s^{-1}.

In Eq. (1), dynamic variables include inside and outside temperature, ventilation rate, and heater input. The first is the system output from the model, and the latter are system inputs to the model at each time step. Adjustable parameters included $\dot{V}$, UA, ρ, and q_{internal}, and were specified at the start of each simulation. This equation was integrated with a fixed time step Runge–Kutta algorithm. For simplicity, the time step also represents the sampling time T_s of the controller.

Heating and/or ventilating rates are determined at each time step from either a conventional staging controller (CSC) or a fuzzy logic controller (FLC). An example for the FLC is given in Fig. 1, which shows the overall building/controller model in schematic form. The building temperature is used in a feedback loop, the

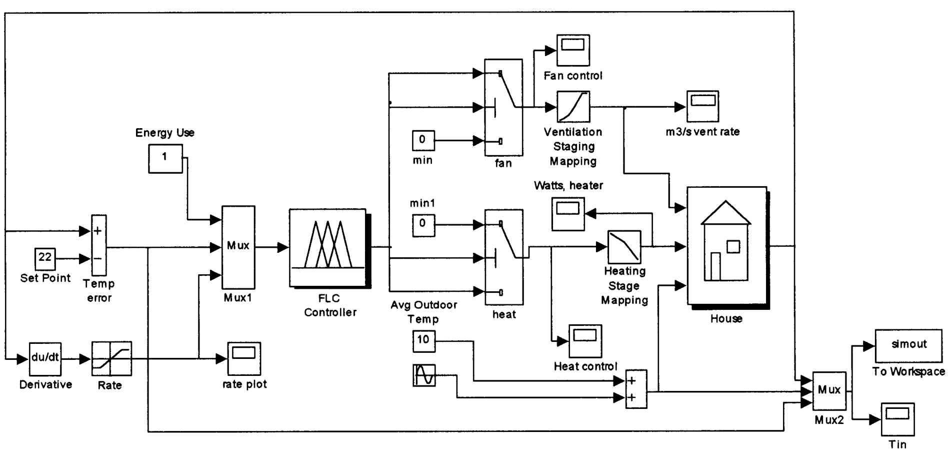

Fig. 1. Block diagram of a building heating and ventilation system, with a 3-input fuzzy logic controller (FLC). For the conventional stage controller (CSC), the FLC block was replaced. For simpler FLC models, the number of inputs were reduced as explained in the text.

Table 1
Building and simulation parameters

Building parameters	Symbol	Value
Heat losses	UA	1868 W K^{-1}
Dimensions		$12 \times 156 \times 2.4$ m
Volume	V	4500 m^3
Heat production (30 000 Birds)	q_{internal}	[0, 150, 300] kW
Ventilation stages (0–6)	$\dot{V}$	[4.7, 9.4, 18.8, 37.6, 56.4, 75.2, 75.2] m^3 s^{-1}
Heating stages	q_{heater}	[300, 200, 0] kW
Minimum ventilation		Stage '0' of ventilation
Air density	ρ	1.2 kg m^{-3}
Specific heat	C_p	1006 J $kg^{-1}K^{-1}$
Stages	CSC	[−1 0 1 2 3 4 5 6]
	FLC	[−2 −1 0 1 2 3 4 5 6]
Stage differential	CSC	1 K
	FLC	Variable, according to fuzzy inference

setpoint temperature is subtracted, and the resultant control error is sent to a multiplexer and then to the controller (FLC or CSC). Controller output is a discrete number $\{-2, -1, \ldots, 5, 6\}$ representing relay(s) activation. The two switch blocks and their lookup tables determine what values for heat and ventilation are sent to the building model at each time step. Outside temperature varies according to a simple sinusoidal function selected to exercise both cooling and heating modes of the controller model. Internal heat load is varied from zero (small birds) to 300 kW (mature broilers at typical stocking densities) according to Gates et al. (1996).

2.2. Discrete controllers for staged ventilation systems

2.2.1. Conventional staging controller (CSC)

The CSC maps control error to desired stages of heating and/or cooling (Chao et al., 1995; Chao and Gates, 1996). The example CSC configuration for a broiler house is given in Table 1. The configurations and equipment capacities are from Gates et al. (1996), with 1 K increment between stages.

As an example, if current inside temperature is 4°C above the setpoint, then the CSC model will send this error into the controller block, which maps the 4°C error into a discrete number, 3, representing the ventilation stage level necessary. Stage 3 corresponds to a ventilation rate of 37.6 m^3 s^{-1} and zero heating rate. The building model uses these energy inputs, the current temperature, the outside temperature and other parameters in Eq. (1) to determine the inside temperature for the next time step. Under steady state conditions there will typically be a steady state building temperature T, which differs from the set point temperature.

2.2.2. Fuzzy logic controller (FLC)

In a similar manner, a FLC will map inputs to control responses. Several different types of inputs will be presented in this paper, ranging from a simple P

(Proportional) controller to a more involved PI (Proportional and Integral) controller. Note that the main complexity of implementing a FLC involves incorporation of the discrete nature of the staged heating/ventilating equipment. The fuzzy logic process used in this work implemented five operations:

1. fuzzify numerical inputs using input membership functions
2. apply fuzzy operators to the antecedents of the rule base
3. perform implication, i.e. shape the consequent portion of the rules
4. aggregate each rule's output into a common fuzzy set, and
5. de-fuzzify the aggregate fuzzy set to obtain control output using a center of gravity output rounded to the nearest integer.

A rule base maps linguistic inputs to outputs and the fuzzy process quantifies these actions.

Each FLC presented in this paper involves different combinations of input variables, membership functions, and rule bases. Interpretation of the FLC performance and design optimization of FLC configuration can be enhanced by determining appropriate design parameters. Controller response, including response to step change in setpoint and behavior under a widely varying external temperature load, can be used to compare different designs.

For the FLC depicted in Fig. 1, there are three inputs to the FLC: temperature error, energy use, and rate. This is referred to as the 3-input FLC in this paper. These three inputs are multiplexed and sent to the 3-input FLC block which in turn maps these inputs to a desired output as explained previously. For example, if the FLC output were stage 6, then the ventilation rate would be 75.2 $m^3\ s^{-1}$, and the heating rate would be zero. The connection between inputs and outputs, both of which are 'crisp' values, is made via the linguistic transformation of inputs using input membership functions, implication and aggregation using the rule base, and de-fuzzification of the linguistic output to a numerical value representing stage of ventilation.

3. Design parameters

3.1. Staged FLC theory

With careful selection of process state variables and control variables, and the contents of the rule-antecedent and rule-consequent for each of the rules, a P- or PI-like FLC can be designed. The process state variables representing the contents of the rule-antecedent (*if-part* of a rule) can be selected as:

e: error for P-like FLC
Δe: change of error for PI-like FLC

Control variables evolve from the rule consequent (*then-part* of the rule), and can be selected as:

u: control output for P-like FLC
Δu: change of error for PI-like FLC

For a conventional digital controller design, the error and change of error can be defined as:

$$e(k) = y_{sp} - y(k) \tag{2}$$

$$\Delta e(k) = e(k) - e(k-1), \tag{3}$$

where y_{sp} is the set point of the process, k is the sampling time.

The equation for a P-controller is:

$$u = K_P e \tag{4}$$

where K_P is the proportional gain coefficient.

The symbolic representation of a rule for a P-like FLC can be formulated as:

If e is ⟨linguistic description⟩*then* u is ⟨linguistic description⟩ (5)

The equation governing a conventional PI-controller is:

$$u = K_P e + K_I \int e \, dt \tag{6}$$

where K_P and K_I are the proportional and the integral gain coefficients.

The symbolic representation of a rule for a PI-like FLC can be formulated as:

If e is ⟨linguistic description⟩*and* Δe is ⟨linguistic description⟩

then Δu is ⟨linguistic description⟩. (7)

Note that $u(k)$ will be the sum of $u(k-1)$ and Δu.

The design strategy stated above is useful for designing a P- or PI-type FLC with continuous output devices such as variable speed fans, hot water heating systems, or air inlets. For control systems with discontinuous output states (such as encountered in staged ventilation control systems), the concept of a P-type FLC is easily understood. However, direct implementation of a PI-type FLC based on the design concept listed in Eq. (7) is not straightforward for staged ventilation control systems. The reason is simply that there are no intermediate variables between two adjacent stages. Thus, calculating a small integral error and using it to reduce steady state error is not applicable in the staging control scheme. Instead of implementing inference rules to calculate Δu, a set of input membership functions that are closely overlapped with each other can be built for tight control. Then, the steady state errors are expected to be small. The shape of resultant response curves can be used to assess the design feasibility.

3.2. Developing the FLC

3.2.1. Case 1: one-input FLC

To demonstrate the design of a FLC, consider a simple system which consists of a one-input and one-output FLC. The input, control error, is identical to that provided to the CSC. Input membership functions for the control error use six linguistic variables to apportion over the range of -5 to $+10$ K error (NBD,

Table 2
Rule base for the simple fuzzy logic controller (FLC) with 6 rules

Control error	Consequent
PBD	Cooling-high
PMD	Cooling-medium
PSD	Cooling-low
ZD	No-change
NSD	Heat 1
NBD	Heat 2

NSD, ZD, PSD, PMD, and PBD), following a method that is customary in the literature (e.g. Gates et al., 1997). For example, NBD refers to a Negative Big Difference between inside temperature and setpoint, i.e. it is much colder than desired in the building. The rule base for the simple FLC is given in Table 2. Each possible linguistic value of input control error is assigned a consequential action; for example if control error is PBD then control action is 'cooling-high'.

3.2.2. Case 2: two-input FLC

A second, user-defined input labeled Energy Use, ranges from 0 to 1 (Fig. 1). It provides a user's relative importance attached to energy consumption vs. control precision. A value near 0 indicates that energy use should be low; a value near unity suggests that minimal control error is desired. The input membership function for the energy use input consists of three linguistic variables (Low, Ok, High). The input membership function for control error is broken into seven linguistic variables by splitting the deadband Zero Difference (ZD) term for the one Input FLC into a positive and a negative term: 'PZD' and 'NZD'. A more comprehensive rule base (Table 3) is required, consisting of 21 possible values (3 Energy Use $\times$ 7 Control Error). Some redundancies in combinations result in 16 unique rules, as listed in Table 3.

Table 3
Rule base for 2-Input FLC (STAGEFLCX1.FIS) with 21 rules

Control error	Energy use input		
	Low	Ok	High
PBD	Cooling-high	Cooling-high	Cooling-high
PMD	Cooling-low	Cooling-medium	Cooling-high
PSD	No change	Cooling-low	Cooling-medium
PZD	No change	No change	Cooling-low
NZD	No change	No change	Heat 1
NSD	No change	Heat 1	Heat 2
NBD	Heat 2	Heat 2	Heat 2

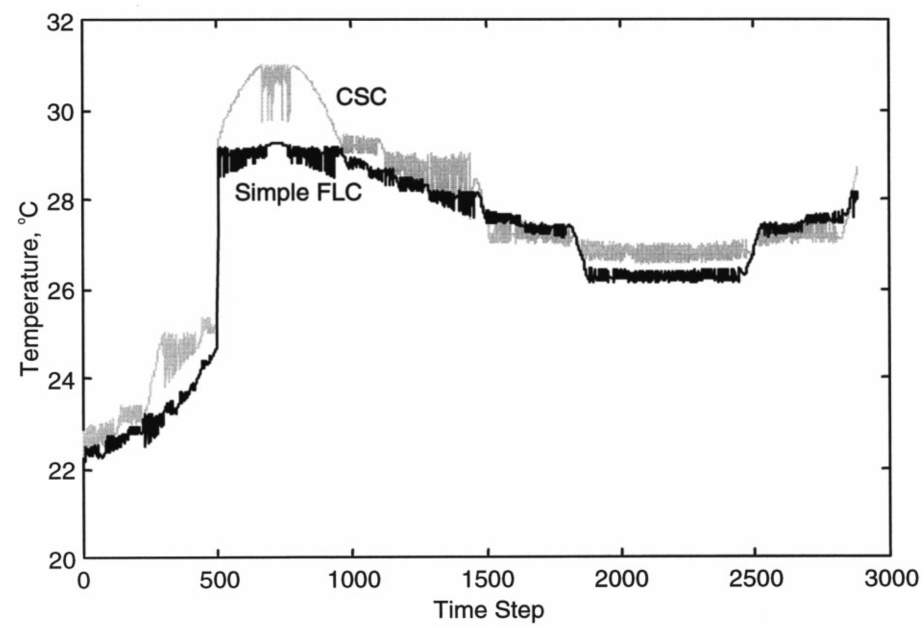

Fig. 2. Step response for the FLC compared with the CSC.

3.2.3. Case 3: three-input FLC

To further generalize the ability of the FLC, a third input, Rate, i.e. the time derivative of the building temperature, $T(t)$, was added. The intent is to provide some damping as the system responds to energy inputs, and to reduce both overshoot and the amplitude of control error oscillations noted in Figs. 2–4. For example, if control error is PBD then Cooling-High has high degree of membership. If overshoot is anticipated, then as Rate becomes negative (i.e. cooling commences), the system instead selects Cooling-Medium to anticipate overshoot. Thus, the Rate membership function consists of two levels: Negative and Positive, ranging over ± 0.05 K s^{-1}. This magnitude was selected to ensure a maximum change of 1.5 K during a single 30 s control interval. Table 4 includes 5 of 35 rules in the rule base to demonstrate the concept.

4. Simulations

4.1. Broiler house simulations

A conventional tunnel ventilated broiler house with parameters given in Table 1 was used to perform a sensitivity analysis and comparison of the CSC and FLC systems. These facilities experience a tremendous range in thermal loads on the interior environment as birds mature and as outside conditions vary. Heating and

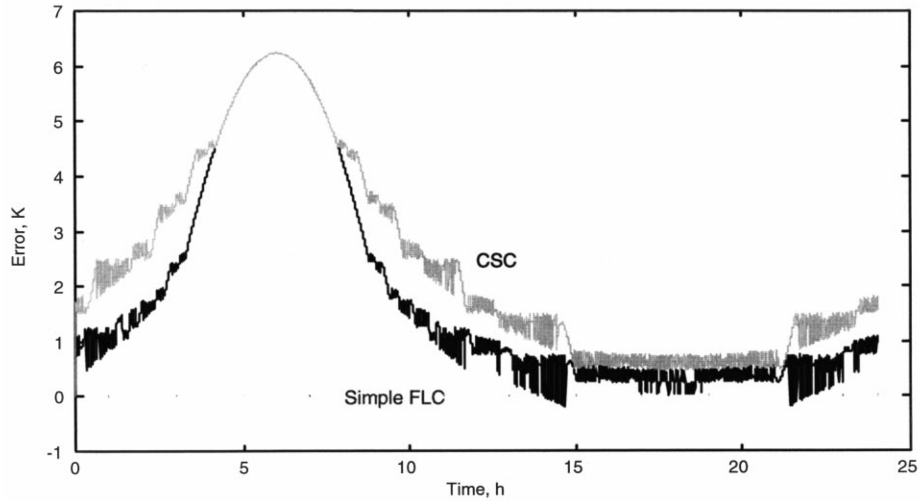

Fig. 3. Simulated temperature error for the 1-input FLC compared with the CSC.

ventilation equipment are generally sized for extreme conditions: heaters for a design outdoor cold temperature with no bird heat, and ventilation for a design outdoor hot condition with maximum sized birds. Each case was simulated for each controller, with outside temperature varying from −5 to 25°C, and a 30 s fixed time step. Setpoint was fixed at 22°C. System response to a 6 K step change in setpoint was analyzed.

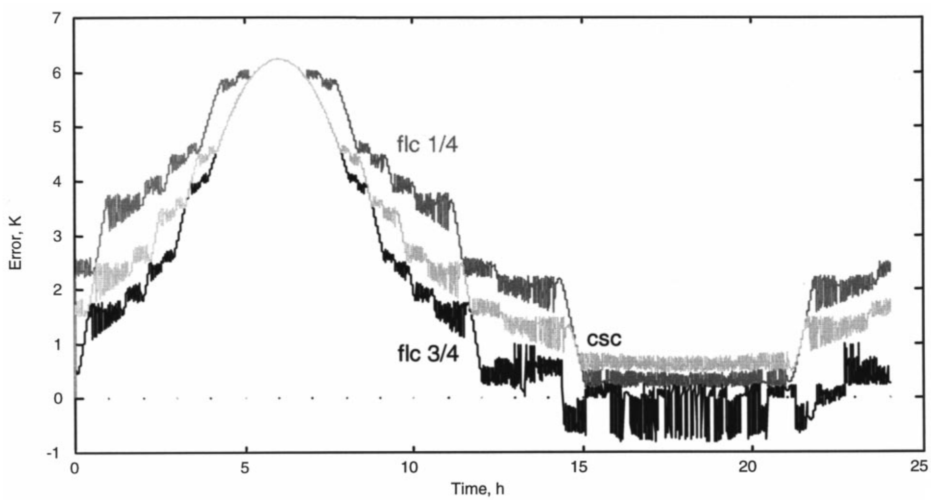

Fig. 4. Simulated temperature error for the 2-input FLC compared with the CSC.

Table 4
Example rules in 3-input FLC with control error rate input

If (Energy use is high) and (Control error) is	And rate is	*Then* stage is
NZD	Positive	No change
NSD	–	Heat 1
NSD	Negative	Heat 2
NBD	–	Heat 1
NBD	Negative	Heat 2

4.2. Simulation results

4.2.1. Case 1: one-input FLC

A comparison of system transient response to a step change of 6 K at time step 500 (setpoint 22–28°C) is shown in Fig. 2. The simple one input FLC reaches the settling time (defined as $\pm 10\%$ of the final value of 28°C) very quickly. However, the CSC required almost 500 simulated time steps to reach and remain within a tolerance zone around the final value. Thus, while both control systems can be characterized as unconditionally stable (Zhang et al., 1993b), the fuzzy controller exhibits superior recovery from the setpoint disturbance compared with the CSC. As outside temperature drops below 28°C, both controllers track a similar course and exhibit some steady-state error.

For a constant setpoint of 22°C, the resultant control error for the simple FLC and CSC is provided in Fig. 3. Both systems lose temperature control as outside temperature rises to near the desired interior temperature. The FLC reduces control error compared with the CSC; however it also exhibits greater oscillations during transition between heating and cooling. Both exhibit steady-state errors when night time temperatures are low.

4.2.2. Case 2: two-input FLC

The resultant control error history for the simulated diurnal cycle (Fig. 4) indicates that the second input (Energy Use) allows the controller to span the conventional staging controller behavior. For example, with Energy Use set to 0.75 the interior temperature keeps closer to setpoint (with more equipment switching); whereas with Energy Use set to 0.25, considerable excursions from setpoint are realized. The CSC temperature falls roughly between these two FLC curves except during heating mode, where low Energy Use (0.25) results in minimal switching and a smaller steady-state error compared with CSC.

In contrast to the results seen in Fig. 3, this two input FLC with Energy Use = 0.75 allows a more discontinuous control error than either the simple one input FLC or the CSC. Both FLCs give improved RMS errors compared with the CSC (Table 5) for this widely varying diurnal outside temperature test.

Table 5
Summary of controller performance

Controller	Q_{internal} (kW)	RMS error (K)	Minimum error (K)	Maximum error (K)
CSC	0	1.1	−1.0	3.0
	100	1.9	−0.6	4.4
	200	2.4	−0.5	5.2
	300	3.0	0.5	6.2
1-input FLC (energy input = 1)	0	1.1	−1.0	3.0
	300	2.6	−0.2	6.2
3-input FLC (energy input = 1)	0	1.0	−0.8	3.0
	300	2.6	−1.4	6.2
3-input FLC (energy input = 0.5)	0	1.4	−1.6	3.0
	300	3.0	0.6	6.2
3-input FLC (energy input = 0)	0	2.7	−3.4	3.0
	300	4.0	2.2	6.2

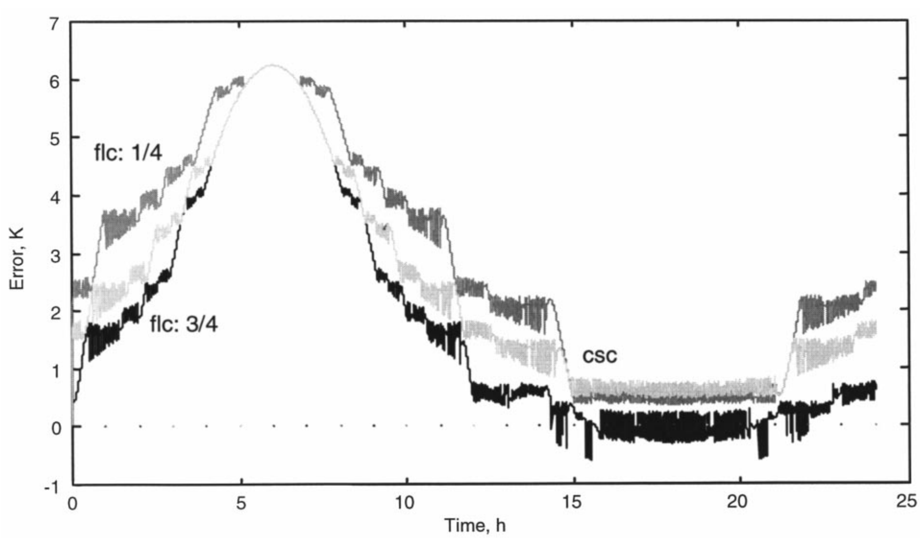

Fig. 5. Simulated temperature error for a 3-input FLC compared with the CSC.

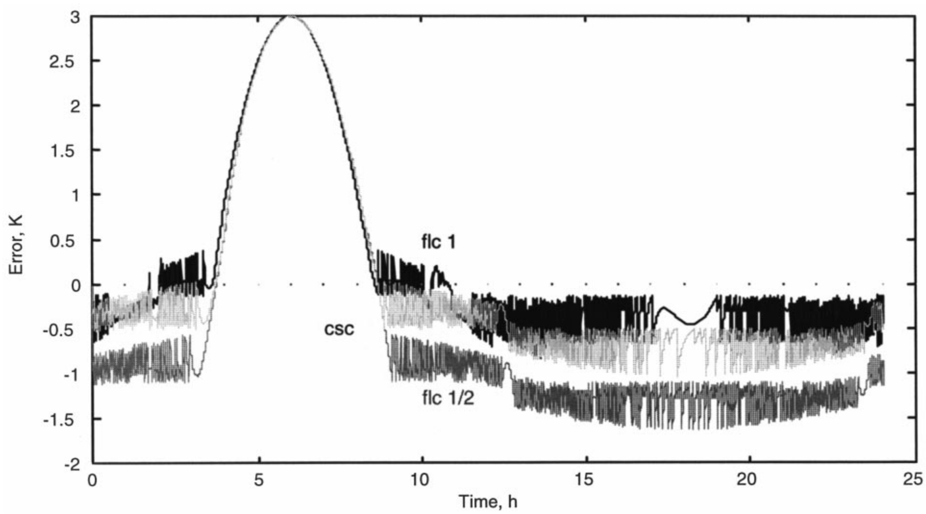

Fig. 6. Simulated temperature error for the 3-input FLC with no internal heat load as compared with the CSC.

4.2.3. Case 3: three-input FLC

Results from a diurnal simulation with identical inputs as in the previous two cases, indicate that the 3-input FLC has improved switching performance and reduced offset error during heating (Fig. 5). Additional simulation results are presented in Fig. 6, with Energy Use = {0.5, 1.0}, and with the CSC response for comparison. Internal heat load was set to zero, such as occurs during early stages of growout. All other pertinent variables are given in Table 1. Results demonstrate:

1. loss of temperature control during the hottest portion of the day occurred for all systems,
2. night time errors were less than 1.5 K for all systems, with the 3-input FLC (energy use = 0.5) having largest errors, followed by the CSC, and the 3-input FLC (energy use = 1) having small negative errors (> -0.5 K).
3. increasing the internal heat load resulted in increased magnitude of daytime control error for all systems, and decreased night time control error magnitude (Fig. 4 vs. Fig. 5).
4. the 3-input FLC was able to keep the root-mean-square error (RMS) in the range 1.0–2.7 K, depending on Energy Use settings and internal heat load. In contrast, CSC realized substantially larger daytime, and slightly larger night time, control errors, with RMS error = 1.1 K.

5. Discussion

A summary of the three controllers' performance statistics for the simulated 24 h diurnal cycle are presented in Table 5. The simple one input FLC performed quite well compared with the CSC and with the 3-Input FLC. No control system could reduce maximum control error at high internal heat load as outside temperature exceeded inside set point. The trend for the CSC, as internal heat load increased from 0 to 300 kW, was an increased RMS error, and more extreme values of control error. RMS error increased in the 3-Input FLC as the Energy Use input was reduced, with a setting of about 0.5 yielding similar performance to that of the CSC at the same internal heat load.

The concept of the 3-input FLC is straightforward to implement in any CSC utilizing a microprocessor with floating point capability, since the design concept incorporates the discrete nature of existing staged ventilation control systems. Adoption of such a technique has several advantages. A principal advantage is to provide the building operator with a preferential input to balance energy use and control precision. Conventional staged controllers provide this to a limited extent only, by using variable differential temperatures between stages, and cannot approach a zero steady-state control error because there is no means for implementing an integrator into the CSC. Conventional PI controllers are capable of removing steady-state error, but require tuning for each type of facility, and re-tuning if equipment selection changes in a given facility. Further, PI controllers cannot be readily adjusted to balance energy use. In contrast, the FLC designs presented here can be readily incorporated into existing facilities, and the logic is scaleable over a variety of building and equipment sizes. The FLC appears to retain the robustness and flexibility of the CSC, with enhanced control features including recovery from step and diurnal disturbances.

6. Conclusion

The proposed fuzzy logic control technique has the following advantages:

1. Simple user inputs to control system.
2. User has supervisory control without worrying about implementation details.
3. Control system is scaleable over range of building sizes.
4. System provides trade-off between departure from set point and energy use.
5. Building ventilation system configuration with controller is flexible (no stage differentials, hysteresis, etc.).
6. Straightforward modification of existing microprocessor-based conventional stage control systems having floating point capabilities.

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